

Data Analysis, Statistics, Machine Learning

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Data Analysis

What is data analysis?

Summaries of batches of data

Methods for discovering patterns in data

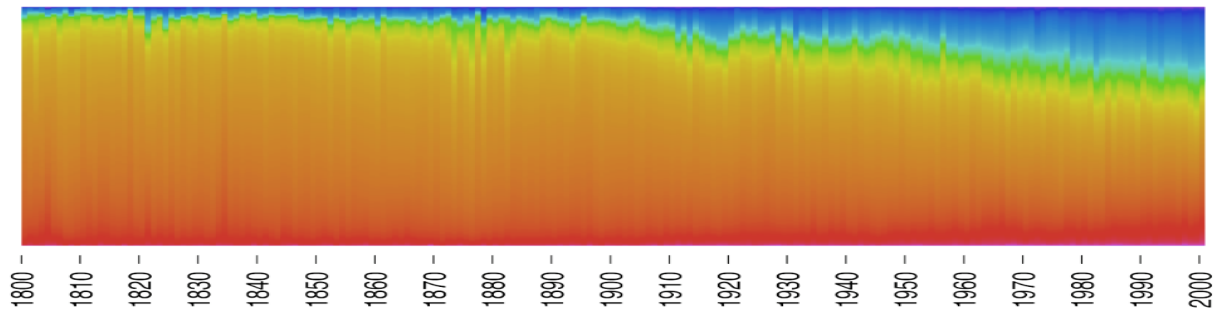
Methods for visualizing data

Benefits

Data analysis helps us support suppositions

Data analysis helps us discredit false explanations

Data analysis helps us generate new ideas to investigate



<http://blog.martinbellander.com/post/115411125748/the-colors-of-paintings-blue-is-the-new-orange>

Statistics

What is (are) statistics?

Summaries of samples from populations

Methods for analyzing samples

Making inferences based on samples

Benefits

Statistics help us avoid false conclusions when evaluating evidence

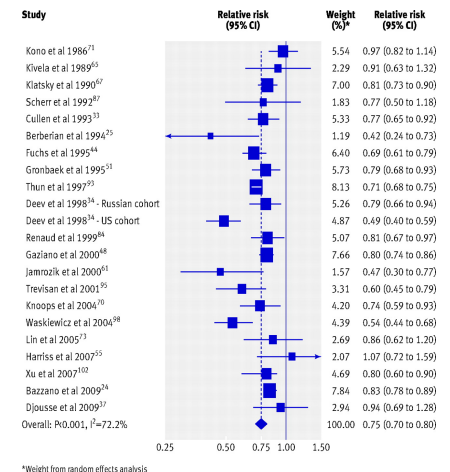
Statistics protect us from being fooled by randomness

Statistics help us find patterns in nonrandom events

Statistics quantify risk

Statistics counteract ingrained bias in human judgment

Statistical models are understandable by humans



<http://www.bmj.com/content/342/bmj.d671>

Machine Learning

What is machine learning?

Data mining systems

Discover patterns in data

Learning systems

Adapt models over time

Benefits

ML helps to predict outcomes

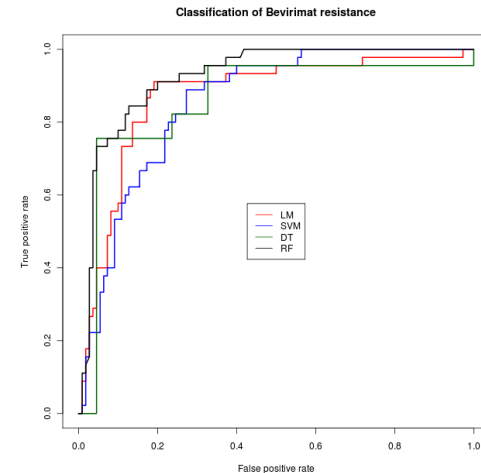
ML often outperforms traditional statistical prediction methods

ML models do not need to be understood by humans

Most ML results are unintelligible (the exceptions prove the rule)

ML people care about the quality of a prediction, not the meaning of the result

ML is hot (Deep Learning!, Big Data!)



http://swift.cmbi.ru.nl/teach/B2/bioinf_24.html

Course Outline

1. Introduction
2. Data
3. Visualizing
4. Exploring
5. Summarizing
6. Distributions
7. Inference
8. Predicting
9. Smoothing
10. Time Series
11. Comparing
12. Reducing
13. Grouping
14. Learning
15. Anomalies
16. Analyzing

Data

What is (are) data?

A datum is a given (as in French donnée)

data is plural of datum

Data may have many different forms

Set, Bag, List, Table, etc.

Many of these forms are amenable to data analysis

None of these forms is suitable for statistical analysis

Statistics operate on variables, not data

A variable is a function mapping data objects to values

A random variable is a variable whose values are each associated with a probability p ($0 \leq p \leq 1$)

Visualizations operate on data or variables

Visualizing

Visualizations represent data

Tallies, stem-and-leaf plots, histograms, pie charts, bar charts, ...

Statistical visualizations represent variables

Probability plots, density plots, ...

Statistical visualizations aid diagnosis of models

Does a variable derive from a given distribution?

Are there outliers and other anomalies?

Are there trends (or periodicity, etc.) across time?

Are there relationships between variables?

Are there clusters of points (cases)?

Exploring

Exploratory Data Analysis (John W. Tukey , *EDA*)

Summaries

Transformations

Smoothing

Robustness

Interactivity

What EDA is not ...

Letting the data speak for itself

Fishing expeditions

Null hypothesis testing

Qualitative Data Analysis

Mixed methods

Old wine in new bottles

Summarizing

We summarize to remove irrelevant detail

We summarize batches of data in a few numbers

We summarize variables through their distributions

The best summaries preserve important information

All summaries sacrifice information (lossy)

Summaries

Location

Popular: mean, median, mode

Others: weighted mean, trimmed mean, ...

Spread

Popular: sd, range

Others: Interquartile Range, Median Absolute Deviation, ...

Shape

Skewness

Kurtosis

Distributions

A probability function is a nonnegative function

Its area (or *mass*) is 1

Distributions are families of probability functions

Most statistical methods depend on distributions

Nonparametric methods are distribution-free

The Normal (Gaussian) distribution is most popular

Other distributions (Binomial, Poisson, ...) are often used

We use the Normal because of the Central Limit Theorem

Variables based on real data are rarely normally distributed

But sums or means of random variables tend to be

So if we are drawing inferences about means, Normal is usually OK

This involves a leap of faith

Inference

Inference involves drawing conclusions from evidence

In logic, the evidence is a set of premises

In data analysis, the evidence is a set of data

In statistics, the evidence is a sample from a population

A population is assumed to have a distribution

The sample is assumed to be random (Sometimes there are ways around that)

The population may be the same size as the sample (not usually a good idea)

There are two historical approaches to statistical inference

Frequentist

Bayesian

There are many widespread abuses of statistical inference

We cherry pick our results (scientists, journals, reporters, ...)

We didn't have a big enough sample to detect a real difference

We think a large sample guarantees accuracy (the bigger the better)

Predicting

Most statistical prediction models take one of two forms

$$y = \sum_j (\beta_j x_j) + \varepsilon \quad (\text{additive function})$$

$$y = f(x_j, \varepsilon) \quad (\text{nonlinear function})$$

The distinction is important

The first form is called an additive model

The second form is called a nonlinear model

Additive models can be curvilinear (if terms are nonlinear)

Nonlinear models cannot be transformed to linear

Examples of linear or linearizable models are

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p + \varepsilon$$

$$y = \alpha e^{\beta x} + \varepsilon$$

Examples of nonlinear models are

$$y = \beta_1 x_1 / \beta_2 x_2 + \varepsilon$$

$$y = \log \beta_1 x_1 \varepsilon$$

Smoothing

Sometimes we want to smooth variables or relations

Tukey phrased this as

data = smooth + rough

The smoothed version should show patterns not evident in raw data

Many of these methods are nonparametric

Some are parametric

But we use them to discover, not to confirm

Time Series

Time series statistics involve random processes over time

Spatial statistics involve random processes over space

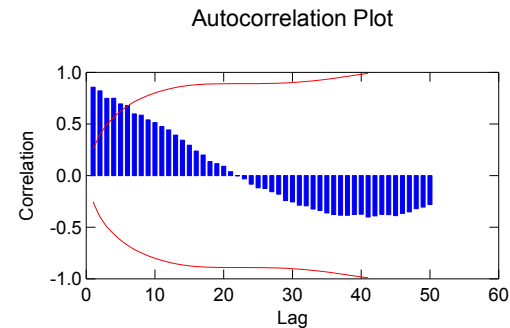
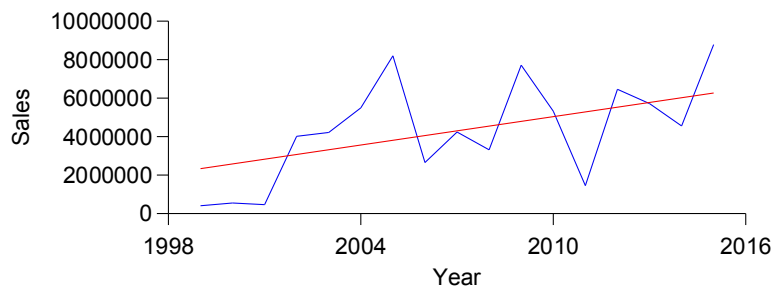
Both involve similar mathematical models

When there is no temporal or spatial influence, these boil down to ordinary statistical methods

DO NOT USE i.i.d. methods on temporal/spatial data

These require stochastic models, not “trend lines”

measurements at each time/space point are not independent



Quarterly US Ecommerce Retail Sales, Seasonally Adjusted

Comparing

Statistical methods exist for comparing 2 or more groups

The classical approach is Analysis of Variance (ANOVA)

This method invented by Sir Ronald Fisher

It revolutionized industrial/scientific experiments

The researcher was able to examine more than one treatment at a time

With only two groups, results of Student's t -test and F -test are equivalent

Multivariate Analysis of Variance (MANOVA)

This is ANOVA for more than one dependent variable (outcome)

Hierarchical modeling is for nested data

There are several forms of this multilevel modeling

Reducing

Reducing takes many variables and reduces them to a smaller number of variables

There are many ways to do this

- Principal components (PC) constructs orthogonal weighted composites based on correlations (covariances) among variables

- Multidimensional Scaling (MDS) embeds them in a low-dimensional space based on distances between variables

- Manifold learning projects them onto a low-dimensional nonlinear manifold

- Random projection is like principal components except the weights are random.

Grouping

We can create groups of variables or groups of cases

These methods involve what we call Cluster Analysis

- Hierarchical methods make trees of nested clusters

- Non-hierarchical methods group cases into k clusters

 - These k clusters may be discrete or overlapping

Two considerations are especially important

- Distance/Dissimilarity measure

- Agglomeration or splitting rule

The collection of clustering methods is huge

- Early applications were for numerical taxonomy in biology

Learning

Machine Learning (ML) methods look for patterns that persist across a large collection of data objects

ML learns from new data

Key concepts

- Curse of dimensionality

- Random projections

- Regularization

- Kernels

- Bootstrap aggregation

- Boosting

- Ensembles

- Validation

Methods

Supervised

- Classification (Discriminant Analysis, Support Vector Machines, Trees, Set Covers)

- Prediction (Regression, Trees, Neural Networks)

Unsupervised

- Neural Networks

- Clustering

- Projections (PC, MDS, Manifold Learning)

Anomalies

Anomalies are, literally, lack of a law (*nomos*)

The best-known anomaly is an outlier

This presumes a distribution with tail(s)

All outliers are anomalies, but not all anomalies are outliers

Identifying outliers is not simple

Almost every software system and statistics text gets it wrong

Other anomalies don't involve distributions

Coding errors in data

Misspellings

Singular events

Often anomalies in residuals are more interesting than the estimated values

Analyzing

What Statistics is not

mathematics

machine learning

computer science

probability theory

Statistical reasoning is rational

Statistics conditions conclusions

Statistics factors out randomness

Wise words

David Moore

Stephen Stigler

TFSI

References

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